

Feature Extraction and Detection of Aorta using Histogram of Oriented Gradients and Support Vector Machines in Cardiac CTA

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Abstract:

In this paper, we propose an automatic aorta detection method in computed tomography angiography (CTA) using Histogram of Oriented Gradients (HOG) and Linear Support Vector Machine (LSVM). For our methods, we trained the LSVM classifier with HOG descriptors which are extracted from cardiac CTA. And we detect aorta region as follows. First, we denoise the images by applying anisotropic diffusion filtering. Second, the feature is extracted from the input image using HOG descriptor. Third, we detect the aorta by LSVM classifier. We tested our method in ten CT images and they were obtained from a different patient. For the evaluation of the computational performance of the proposed method, we measured the total processing time and intersection over union (IOU). The average of total processing time, from first step to third step, was 19.99 ± 1.99 s, and IOU was 0.85 ± 0.05 . We expect for our method to be used in cardiac diagnosis for cardiologist.

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I. Introduction

Object detection is to identify objects of interest in the image and to cluster pixels of the objects [1, 2]. In the field of medicine, it is necessary to detect some organs or tumours from medical images. Computed tomography (CT) is an imaging procedure that uses x-ray technology to produce tomographic images of specific object. CTA, CT angiography and one of medical images which have the information of the heart, is widely used in image segmentation because it provides more detailed anatomic information about the organ [3]. Image segmentation is to extract specific region or divide areas in the image, and it is usually used in medical imaging field [12-17].

The disorders of the heart of blood vessels often cause cardiovascular diseases, and heart segmentation from CTA has been used for cardiac diagnosis [4]. There are several methods for aorta detection. Saur et al. presented an aorta detection method with two-level threshold ray propagation approach [5]. This approach extracted only the whole heart. This method is not robust in noisy images, because only thresholds of intensity are used. Zheng et al. presented a part-based aorta segmentation and valve landmark detection to train detector for each part of aorta [6]. This method requires well-defined labelling mask and landmark dataset which takes too much time and effort to generate a training set. In this paper, we propose an automatic method to detect the aorta using

HOG and LSVM classifier which we develop with only the bounding box data of aorta[7, 8].

The remainder of the paper is organized as follows. The next section describes the proposed method of automatic aorta detection in CTA. This procedure consists of three processing steps. Section III presents the results of the proposed method to clinical dataset. In section IV, we summarize the results and discussion.

II. Materials and Methods

Data sets

We used one hundred data sets of CTA for training, which is augmented from thirty data sets. And ten data sets are examined in this study. The numbers of images per scan ranged from 192 to 227. Each image had a matrix size of 512×512 . The voxel size was 0.36.

Training features

We extract HOG descriptors from our train data set which is denoised with anisotropic diffusion filtering [9]. To train these features for the LSVM we divide the train features into two data sets – one is positive dataset and the other is negative one. We trained the LSVM on our positive and negative datasets and generated binary classifier. For each image and possible scale, we generated image pyramid using Gaussian filtering and sliding window methods. And we computed HOG descriptors at each window and applied our classifier.

Smoothing images

First, we denoised the input CTA. Because the cardiac CTA has much noise and it would not be vivid. So image smoothing is essential to detect object. To remove the noise, we use anisotropic diffusion filtering to preserve the edge while smoothing the original image and preserves finer

detailed structures in images. The equation of anisotropic diffusion filter is as follows.

$$\min TV = \int_{\Omega} \sqrt{u_x^2 + u_y^2} dx dy \quad (2.1)$$

where u is an image, u_x and u_y is the derivative of u w.r.t. x and y respectively. To discretize and optimize this equation, Rudin et al. proposed a method to minimize using gradient descent PDE[10]. Through calculus of variations, the gradient descent PDE of the minimization is as follows.

$$(2.2) \quad \begin{cases} \partial_t u = \operatorname{div} \frac{\nabla u}{|\nabla u|} + \lambda(f - u), \\ \nu \cdot \nabla u = 0 \quad \text{on } \partial\Omega. \end{cases}$$

Since this equation is convex, the steady state solution of the gradient descent is the global optimum. And gradient descent is performed by iterating equation (3).

$$(2.3) \quad \begin{aligned} u_{i,j}^{n+1} = & u_{i,j}^n + dt \left[\nabla_x^- \left(\frac{\nabla_x^+ u_{i,j}^n}{\sqrt{(\nabla_x^+ u_{i,j}^n)^2 + (m(\nabla_y^+ u_{i,j}^n, \nabla_y^- u_{i,j}^n))^2}} \right) \right. \\ & \left. + \nabla_y^- \left(\frac{\nabla_y^+ u_{i,j}^n}{\sqrt{(\nabla_y^+ u_{i,j}^n)^2 + (m(\nabla_x^+ u_{i,j}^n, \nabla_x^- u_{i,j}^n))^2}} \right) \right] + dt \lambda(f_{i,j} - u_{i,j}^n), \quad i, j = 1, \dots, N-1 \end{aligned}$$

Detecting the aorta

To detect the aorta region, we extract HOG descriptor from filtered image and apply our binary classifier. If the classifier detects objects, record the bounding boxes of the window and choose the most probability among the objects with non-maximum suppression [11]. The result of the aorta detection is in Figure 1. We detect two objects and select only one which is bigger than others.

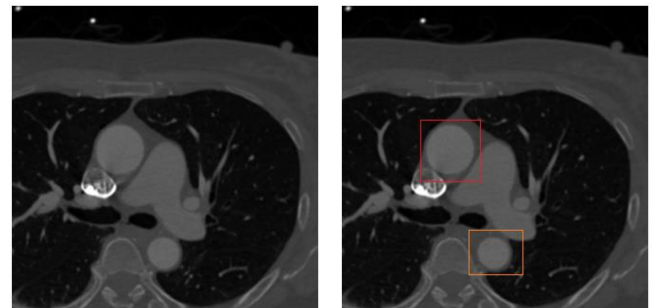


Figure 1. The result of the aorta detection using LSVM. The input image (left) and the result of detection (right, red rectangle is the aorta and

orange rectangle is not the aorta, and only red is selected).

III. Experimental Results

We tested our method using the system which has the Intel® Core™ i9-9900K, Quad 3.6 GHz processor, 16 GB of main memory and Windows 10. We trained one hundred data sets which is augmented by affine transformation and detected the aorta from ten CT images and they were obtained from a different patient. The numbers of images per scan ranged from 192 to 227. Each image had a matrix size of 512×512 . The voxel size was 0.36. Figure 1 shows the result of the aorta detection and Table 1 shows the computational time for each step. For the evaluation of the computational performance of the proposed method, we measured the total processing time. The average of total processing time, from first step to third step, was 19.99 ± 1.99 s. And Table 2 shows the IOU of test data. The average and std. is 0.85 ± 0.05 .

Table 1. Computational Time for Each Detection Step(sec)

Data	Smoothin g image	Extractin g features	Detecting aorta	Total
1	4.2	6.3	7.3	17.8
2	5.2	6.8	8.2	20.2
3	4.3	6.3	7.1	17.7
4	6.2	7.2	9.5	22.9
5	4.9	6.3	7.5	18.7
6	6.5	7.2	9.7	23.4
7	4.7	6.7	8.3	19.7
8	5.1	6.5	8.1	19.7
9	5.2	7.1	9.0	21.3
10	4.6	6.2	7.7	18.5

Table 2. IOU of Test Data.

Data	1	2	3	4	5
IOU	0.82	0.90	0.78	0.86	0.85
Data	6	7	8	9	10
IOU	0.75	0.88	0.87	0.86	0.92

IV. Conclusions

In this paper, we propose an automatic aorta detection method using HOG descriptors and LSVM classifier for binary classification. We used the positive datasets and the negative datasets for improving the performance of detection.

We figure out the limitation of our method. First, we don't have many train datasets, because it is difficult to obtain enough cardiac CTA, therefore we apply data augmentation with affine transformation. We'll obtain more datasets for train and validation datasets in future work. Second, we don't have the positive images relative to the negative images. We'll use more negative datasets for the accuracy of the detection in the future work. Finally, it is hard to detect the aorta since it is small area relatively, and to find the slice in cardiac CTA which has the aorta. In the future work, we'll apply to detect the slice of aorta using thresholding or texture analysis from cardiac CTA, and it is expected to more fast and accurate to detect the aorta.

This paper presented the aorta detection method using HOG and LSVM. This method is expected to be used in cardiac diagnosis.

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